The Emergence of 'Us and Them' in 80 Lines of Code: Modeling Group Genesis in Homogeneous Populations

Running Head: Modeling Group Genesis

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Abstract

Psychological explanations of group genesis often require population heterogeneity in identity or other characteristics, whether deep (e.g., religion) or superficial (e.g., eye color). We use game-theoretical agent-based models to explore group genesis in homogeneous populations, and find robust group formation with just two basic principles: reciprocity and transitivity. These emergent groups demonstrate in-group cooperation and out-group defection, even though agents lack common identity. Group formation increases individual payoffs, and group structure is robust to varying levels of reciprocity and transitivity. Increasing population size increases group size more than group number, and manipulating baseline trust in a population has predictable effects on group genesis. An interactive online demonstration enables first-hand exploration of the parameter space (www.mpmlab.org/groups), and available source code (supplementary materials) provides a guide to implementing psychological agent-based models.

Abstract word count: 129

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Across location and time, humans live together in stable groups that display within-group cooperation and out-group antagonism. Tribes, platoons, countries, sports teams and corporations all persist, favoring “us” over “them.” How do such groups emerge? One answer is that groups form along observable pre-existing differences in physical (e.g., race) or cultural (e.g., language) characteristics. However, such observable differences often emerge as a *result* of people already living in distinct groups, making this answer somewhat circular. We suggest that groups can emerge in completely homogeneous populations of interacting agents as long as two simple conditions are met: reciprocity and transitivity. We use agent-based modeling to show that repeated network interaction under these two conditions gives rise to groups. Importantly, these models suggest that group genesis and perpetuation need not require common identity, shared goals, or cultural differences.

Identity and the Problem of Heterogeneous Populations

Social identity is the predominant paradigm for understanding intergroup phenomena (Brewer & Kramer, 1985; Dovidio, Gaertner, & Validzic, 1998; Tajfel, 1982). In this framework, groups are defined in terms of those who identify themselves as members of the group (Reicher, 1982). Such identification, whether based upon deep (e.g., religion or race) or superficial (e.g., eye color or art preferences) characteristics, predicts both in-group favoritism and out-group antagonism (Brewer & Kramer, 1985; Harmon-Jones, Greenberg, Solomon, & Simon, 1996; Tajfel, Billig, Bundy, & Flament, 1971). Social identity provides an intuitive way of understanding group formation, but identity-based groups—even minimal groups—require pre-existing differences among people (i.e., population heterogeneity), whether fundamental (Kunda, 1999) or superficial (Efferson, Lalive, & Fehr, 2008). Although people differ along many dimensions (such as race, language, religion, and political orientation) such differences often arise on the basis of *pre-existing* grouping—if only via geographical separation (Howells et al., 1966). This suggests potential circularity in the role of social identity in the genesis of groups: groups form because people are different, but people are different because they belong to different groups. To escape this circularity, we examine whether groups form in completely homogeneous populations through the interaction of two basic principles of social interaction.

Conditions for Group Genesis: Reciprocity and Transitivity

Reciprocity—A helps/harms B, and B in turn helps/harms A—is a ubiquitous feature of life for organisms ranging from vampire bats and birds to monkeys and humans (Fudenberg, Rand, & Dreber, 2012; Olendorf, Getty, & Scribner, 2004; Schino & Aureli, 2009; Trivers, 2006; Wilkinson, 1984) . As reciprocity depends upon repeated interactions over time (Trivers, 1971), it occurs more frequently between entities who are interpersonally close (e.g., neighbors) rather than distant (e.g., foreign pen pals). Reciprocity is not only a consequence of interpersonal closeness, but also a cause, with people preferring to interact more with (i.e., move closer to) those who cooperate with them (Rand, Arbesman, & Christakis, 2011; Van Lange & Visser, 1999; Wang, Suri, & Watts, 2012).

Transitivity is the phenomenon that individuals generally share their friends' opinions of others (Louch, 2000). Imagine a triad of people—A, B, and C. If A and B are friends, and A (dis)likes C, then B should also (dis)like C. In short, triads should be balanced such that friends of friends should be your friends, and enemies of your friends should be your enemies (Heider, 1958).[1] When triads are unbalanced (e.g., hating your spouse's best friend), dissonance results

[1] Balance theory also suggests that the enemy of your enemy is your friend; the enemy of your enemy, however, may simply be a jerk and therefore *everyone's* enemy.

(Moore, 1978), causing one person to change his or her opinion—typically the one who cares least (Davis, 1963). If A slightly likes C, but B completely hates C, A's opinion is more changeable than B's.

We suggest that these two phenomena—reciprocity and transitivity—are sufficient for the emergence of groups within homogeneous populations. More concretely, groups should spontaneously evolve when: 1) people move closer to those who cooperate with them, 2) people cooperate more with those who are closer to them, and 3) people move closer to their friends' friends and move further from their friends' enemies.[2] The effects of reciprocity and transitivity are well documented in isolation (Bó, 2005; Davis, 1970; Fudenberg et al., 2012; Holland & Leinhardt, 1971), and we suggest that their repeated combination can transform a population of identity-blind agents into stable, cohesive groups that favor the in-group over the out-group.

Analytic Approach

Psychological research on social dynamics often examines one-time dyadic interactions in isolation, but intergroup phenomena often emerge from the repeated interaction of multiple individuals over time. Studying these multi-agent phenomena was once prohibitively time consuming (Sherif, 1961), but modern computational techniques can simulate emergent phenomena through agent-based modeling. Agent-based models are programs in which simulated individuals (agents) interact through time according to simple rules (Bonabeau, 2002; Macy & Willer, 2002; Smith & Conrey, 2007). Although models are rule-based, the large number of simulated individuals and interactions allows the emergence of behavioral patterns that are non-obvious given the governing principles (Marsella, Pynadath, & Read, 2004; A.

[2] We treat distance (both physical and emotional) as isomorphic with probability of interaction: people interact with proximate others more than distant others, and with liked others more than disliked others.

Nowak, Szamrej, & Latané, 1990; Smith & Conrey, 2007; Vallacher, Read, & Nowak, 2002). Agent-based modeling has been used, for example, to examine the density at which crowds turn lethal (Seabrook, 2011), the origins of preferences for fairness (Rand, Tarnita, Ohtsuki, & Nowak, 2013), and the manner in which people pair with romantic partners (Kalick & Hamilton, 1986).

We use agent-based modeling to examine whether reciprocity and transitivity induce group formation in homogeneous populations. Consistent with previous research on the evolution of cooperation in biology, psychology, and economics (Axelrod & Hamilton, 1981; Fudenberg & Maskin, 1986; M. A. Nowak & Sigmund, 1992; Van Lange, Ouwerkerk, & Tazelaar, 2002), we use a prisoner's dilemma game to represent cooperative interactions between agents. In a single prisoner's dilemma, two people interact, each with the choice to cooperate or defect. Cooperators pay a cost to give a larger benefit to the other person, whereas defectors maximize their payoff at the expense of the other player. This simple game captures the essence of social dilemmas: the tension between what is best for the individual (defection) and what is best for the group (cooperation). See Figure 1 for the payoffs in our simulations.

Although defection maximizes payoffs in a single prisoner's dilemma, repeated interactions allow for reciprocity to develop over time (Fudenberg & Maskin, 1986; Rand & Nowak, 2013; Trivers, 1971). If two people see each other often, it can be payoff-maximizing for one person to cooperate today in order to earn another's reciprocal cooperation tomorrow. Importantly, reciprocal strategies can occur through changing relational closeness (Rand et al., 2011; Van Lange & Visser, 1999): if you cooperate (defect), I am more (less) inclined to interact with you in the future.

		Player 2's choice	
		Cooperate	Defect
Player 1's choice	Cooperate	1	-3
	Defect	3	-1

Player 1's payoff

Figure 1. Summary of the prisoner's dilemma payoffs used in simulations. Cooperation makes the dyad as a whole better off, but is individually costly because defection maximizes individual payoffs within a single round.

In our simulations, agents play a series of prisoner's dilemmas within an initially uniform network (i.e., all agents start equally close to one another). The probability of both interaction and cooperation is proportional to closeness, or how much players "like" each other (i.e., *close others are those I see often and to whom I am nice*). Reciprocity is instantiated by allowing agents to adjust closeness to their partner after each interaction (i.e., *he was nice, so I will move closer*). Transitivity is instantiated by allowing agents to adjust their closeness with third parties based on their partner's preferences after each cooperative interaction (e.g., *he was nice to me and he is friends with her, so I will move closer to her too*). These agent-based simulations provide a formal proof of concept of whether reciprocity and transitivity can induce group genesis in homogeneous populations.

To evaluate the generalizability of these models, we examine two additional variables: individual payoffs and trust/suspicion. The prevalence and apparent benefits of groups within diverse evolutionary settings (Olson, 1965) suggest that groups increase individual payoffs. We measure payoffs in our simulations, predicting that conditions conducive to group genesis—the presence of reciprocity and transitivity—will yield higher individual payoffs than conditions unfavorable to group genesis. We also manipulated the population level of trust/suspicion in our model by varying agents' baseline likelihood of cooperation in the prisoner's dilemma. We predicted that more trusting agents (i.e., those who more readily cooperate in a prisoner's dilemma) would form large inclusive groups (like communes), and more suspicious agents would form small, splintered groups (like terrorist cells).

In addition to making a theoretical contribution to our understanding of group genesis and perpetuation, we hope to make agent-based modeling more accessible to psychological science by providing a commented version of our MATLAB code (Supplemental Materials)—a concrete example to complement other guides (Smith & Conrey, 2007). To further emphasize the flexibility of agent-based modeling, we provide an interactive website based on this code, where researchers can experiment with our parameters to explore their effect on group genesis: www.mpmlab.org/groups.

Method: Translating Reciprocity and Transitivity into Code

Conceptual Summary: Imagine a group of identity-less strangers airlifted to a desert island. As they roam, they occasionally run into one another, and when they do, they each have the chance to cooperate or defect. If both cooperate, they become friends and try to see each other more often; if both defect, they become enemies and try to see each other less often (*reciprocity*). If one defects and the other cooperates, there is no change in overall closeness because although the cooperator dislikes being taken advantage of, the defector likes a sucker. As people become friends (enemies), they become more likely to cooperate (defect) when they happen to meet. Friends also have the chance to learn what the other thinks of third parties (akin to gossip in the real world), and can adjust their preferences accordingly: they move closer to their friends' friends and further from their friends' enemies (*transitivity*). We suggest that repeated interaction of reciprocity and transitivity will rapidly transform selfish, identity-blind agents into stable groups. We computationally test this idea in four steps.

1. *Probability of interaction.* The closeness between players is represented by a symmetric matrix *C*. Each cell represents the closeness of player *n* (column) and player *m* (row). Thus, the cell C(4,5) (equal to the cell C(5,4) because the matrix is symmetric) represents the likelihood that players 4 and 5 interact. Initially, all these cells are set to .5 (range: 0 to 1), such that all players are neither close nor far from each other (i.e., indifferent). Each round, a random pair of players are selected (*n* and *m*) and a random number between 0 and 1 is generated. If the value of C(*n*,*m*) is higher than this random number, players *n* and *m* interact; otherwise they do not, and another pair is randomly selected, with a new random number. In the model, as in real life, higher closeness leads to more interaction.

2. *Interaction behavior and payoffs*. When two players *n* and *m* interact, they play a prisoner's dilemma, each deciding whether to cooperate or defect and each receiving a payoff based on the matrix shown in Figure 1. Two random numbers are generated, one for player *n* and one for player *m*. If the players' closeness—the value of C(*n*,*m*)—is higher than their random number, then that player cooperates. If not, then that player defects. For example, if C(*n*,*m*)=.80, *n*'s random number=.91 and *m*'s random number=.15, then *n* defects and *m* cooperates. In the model, as in real life, higher closeness leads to more cooperation.

3. *Reciprocity—moving closer or further from partners (*r*)*. If both players cooperate, they move closer by increasing the value of C(*n*,*m*). The amount by which their closeness increases is determined by the reciprocity mobility parameter *r*: the distance between C(*n,m*) and 1 is divided by *r*. If C(*n*,*m*)=.70 and *r*=2, then mutually cooperating players would halve the distance between their current value and the maximum closeness value of 1, yielding of C(*n*,*m*)=.85. If *r*=3, then this distance is divided by three, yielding C(*n*,*m*)=.90. Conversely, if both players defect, they move away by reducing the difference between their current closeness and the minimum closeness value of 0 by a factor of *r*. For example, after mutual defection at C(*n*,*m*)=.70, a value of *r*=2 would result in a new C(*n*,*m*)=.35. No change in C(*n,m*) occurs when one player cooperates while the other defects. In sum, *r* represents the tendency of players to reciprocate by changing their future interaction probabilities; values of *r*>1 instantiate reciprocity.

4. *Transitivity (*t*)*. If both players cooperate, then transitivity operates and players compare their closeness to all other players other than themselves. In other words, if *n* and *m* both cooperated, they would compare C(*n*,*x*) with C(*m*,x) for all $x \neq n,m$. Whoever of *n* and *m* has the *weaker* opinion (i.e. smaller absolute difference from the midpoint of 0.50) would adjust their closeness to the target player *x* by a factor of *t*, the transitivity mobility factor. For example, if C(*n*,*x*)=.62 and C(*m*,*x*)=.10 (*m* really hates *x* whereas *n* likes *x* only mildly[3]) then, given *t*=2, C(*n*,*x*) would halve to .31. In less mathematical terms, if Fred and Bob cooperated, they would discuss all their mutual acquaintances, and shift their views to be more in line with each other, with more extreme views swaying less extreme views. It should generally be true that *t*<*r* as direct experience with someone (captured by *r*) should shape opinions more strongly than

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[3] .10 is .40 from the midpoint whereas .62 is only .12 from the midpoint.

hearsay (captured by *t*). In sum, *t* represents the mobility of players within transitivity; values of t>1 allow for transitivity.

Steps 1-4 are repeated for as long as desired, but most usefully until the matrix stops appreciably changing (i.e., until groups become stable).

Results: The Genesis of Groups

The results are structured around four specific questions: 1) Do groups form in homogeneous populations under conditions of reciprocity and transitivity? 2) What are the configurations of these groups across parameter space? 3) How are individual payoffs for agents influenced by group-promoting conditions? 4) How does trust influence group genesis? We examine each of these questions across parameter space, averaging 100,000 model iterations of 10,000 generations for each configuration.

Do groups form in homogeneous populations under conditions of reciprocity and transitivity?

Online simulation. The power of reciprocity and transitivity to induce groups can be experienced interactively at www.mpmlab.org/groups/.

Clustering coefficient. To quantify the extent to which our population of agents form groups, we use the standard global clustering coefficient used in network science (e.g., Opsahl & Panzarasa, 2009). This value ranges from 0 to 1, with 0 indicating a complete absence of clustering and 1 indicating the presence of completely distinct groups. Fixing N=50 and varying r and t over the integer values between 1 and 10, we find perfect group formation (clustering coefficient of 1.00) in all simulations in which there is both reciprocity (r>1) and transitivity (t>1). Group genesis is also robust across the number of players (Figure 2).

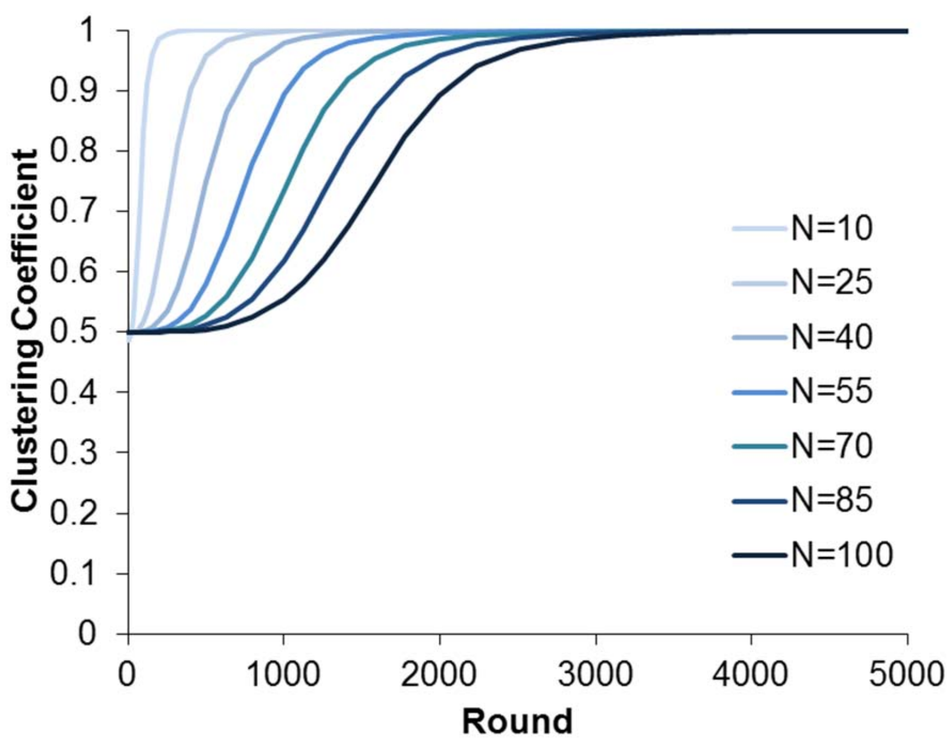

Figure 2. Clustering coefficient through time across variations in number of players (*N*). Simulations use *r*=3 and *t*=2. Each line averages 100,000 simulation runs.

What are the configurations of these groups across parameter space?

Reciprocity (r) *and Transitivity* (t). Fixing *N*=50 and varying *r* and *t* across the parameter space in which groups form (1<*r*≤10, 1<*t*≤10), we find substantial robustness in group configurations. As Figure 3 shows, increasing reciprocity (transitivity) leads to somewhat fewer (more) but larger (smaller) groups, but the effect of this variation is relatively small, suggesting that the dynamics of group genesis are generalizable and not specific to particular levels of reciprocity and transitivity. Of course, as in the real world, there is large variability in group formation across individual simulations. Randomness and path-dependence mean that simulations with identical parameters may lead to one large group, a few single individuals, or two or three similarly-sized groups.

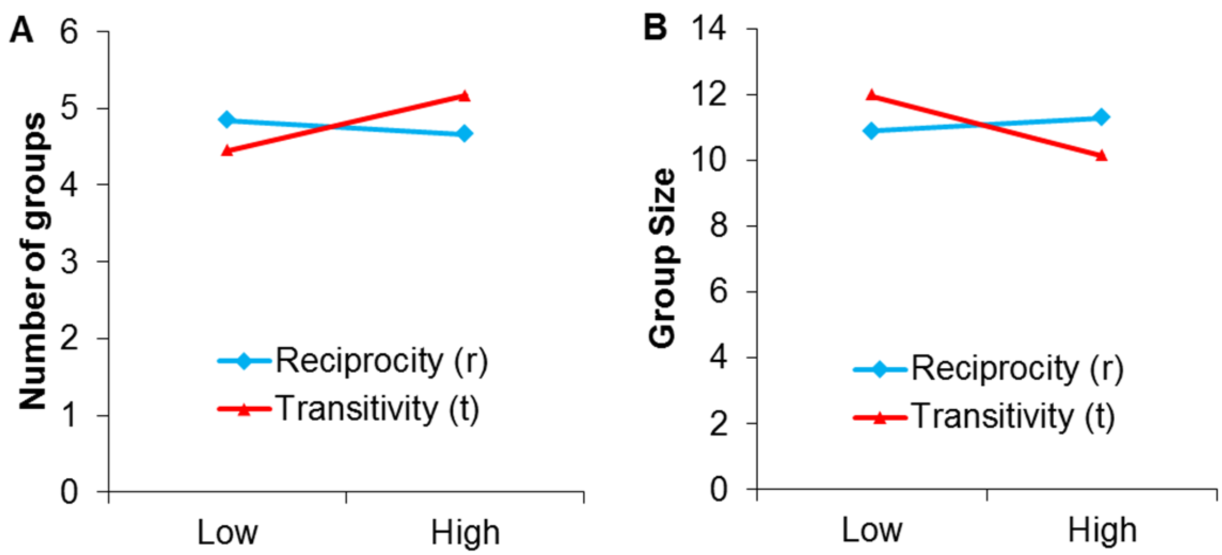

Figure 3. The effect of reciprocity (*r*) and transitivity (*t*) on the average number (A) and size (B) for groups formed. 100,000 model simulations of 10,000 rounds with N=50, and low (2) and high (10) values of *r* and *t*.

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*Number of Players (*N*).* Fixing *r*=3 and *t*=2, *N* was varied between 10 and 100 in increments of 5, and it exert a large influence on group structure. As show in Figure 4, increasing *N* increases both group size and number, but group size increases much more dramatically than group number, suggesting that large populations typically form a small number of large groups rather than a large number of small groups (see Figure 5). This group structure is corroborated by real-world data in the networks literature, from collaboration networks of scientists to the structure of the political blogosphere (Girvan & Newman, 2002; Lazer et al., 2009).

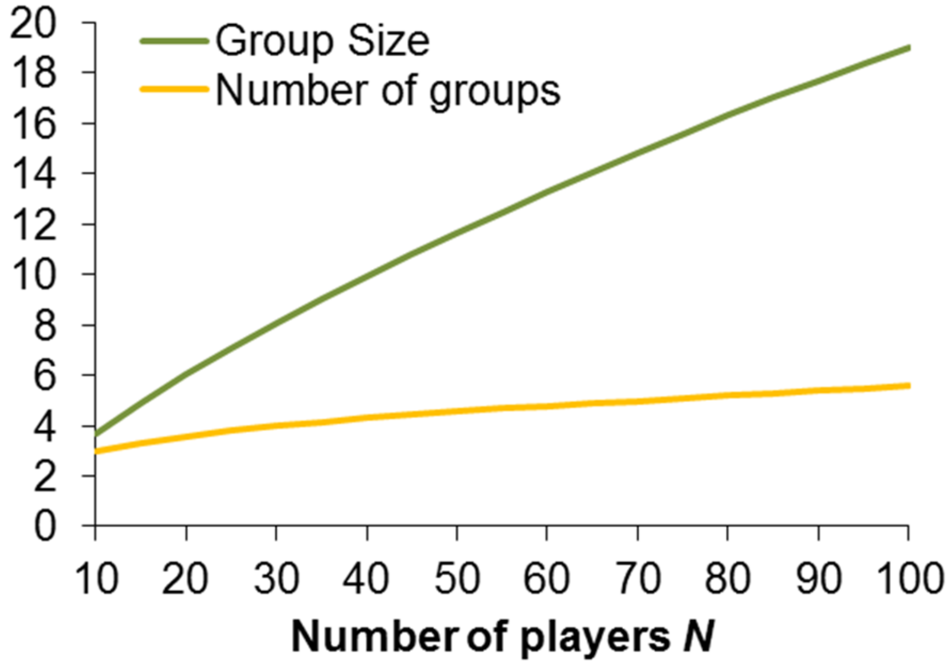

Figure 4. Population size (*N*) affects the number of groups and the average group size in systematic ways. Averaged results over 100,000 simulation runs using *r*=3 and *t*=2, each lasting 10,000 rounds.

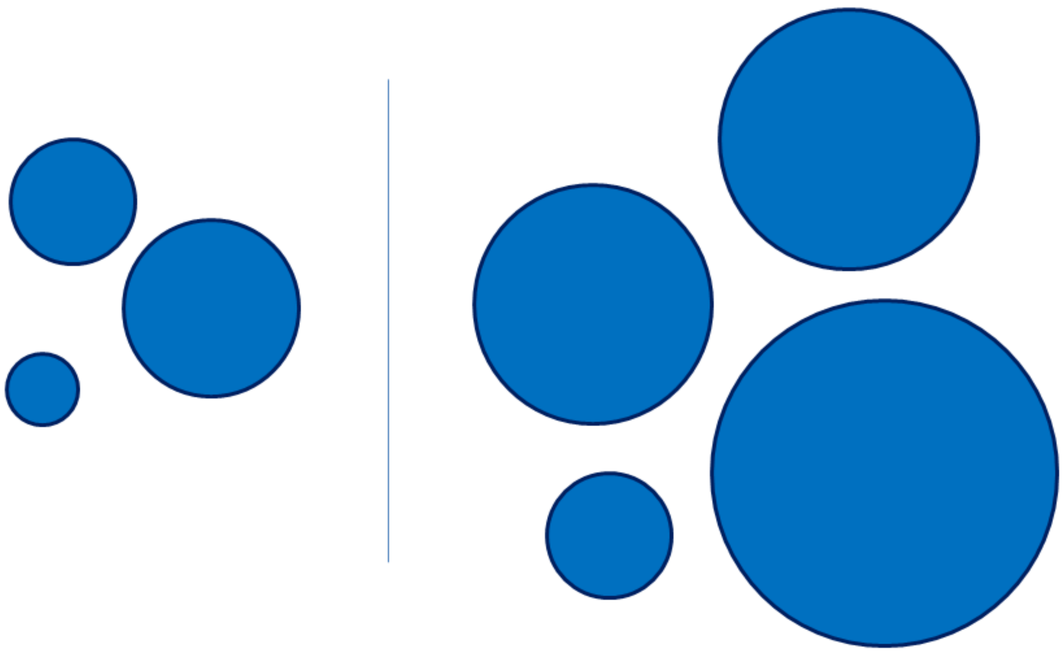

Figure 5. Typical simulation results from two different population sizes. Left, *N*=10; Right, *N*=50. Circle area represents group size with the smallest circle representing a single player.

How are individual payoffs for agents influenced by group-promoting conditions?

Our agents spontaneously form into groups, but are they better off for having done so? Payoffs per opportunity to play (as defined in Figure 1) ranged from -3 to 3, with random strategy selection giving 0 and full cooperation gives 1. Without reciprocity or transitivity (*r*=1; *t*=1; no groups), agents remain indifferent to each other and interact at random, earning an average payoff of 0. The same is true of agents with transitivity but no reciprocity (*r*=1, *t*>1). Reciprocity alone (*r*>1, *t*=0) allows individual pairs of agents to learn to cooperate and increases their average payoff to 0.24. With both reciprocity and transitivity (*r*>1; *t*>1), agents are able to form cooperative groups, leading to the substantially larger average payoff of 0.47. Increasing the population size increases payoffs because larger groups confer more cooperation members, but this effect is relatively small (0.44 at N=10; 0.49 at N=100).

How does trust influence group genesis?

Interpersonal trust was manipulated by adjusting players' baseline cooperation likelihood—given by $C(n,m)$—by adding a constant A. To make players more suspicious, we made their probability of cooperating lower than $C(n,m)$ by defining $A < 0$; to make them more trusting, we made it higher than $C(n,m)$ by defining $A > 0$. In other words, suspicious players cooperate only with relatively closer others, whereas trusting players cooperate even with relatively distant others.

The influence of trust can be examined via the clustering coefficient, as shown in Figure 6. When A is sufficiently negative, suspicion prevents players from cooperating and forming stable bonds, resulting in a landscape of completely isolated individuals (clustering coefficient = 0). When A is sufficiently positive, not only do groups form quickly, but players form one large group (akin to a commune). Thus, group formation is predictably influenced by trust, increasing the psychological generalizability of this model.

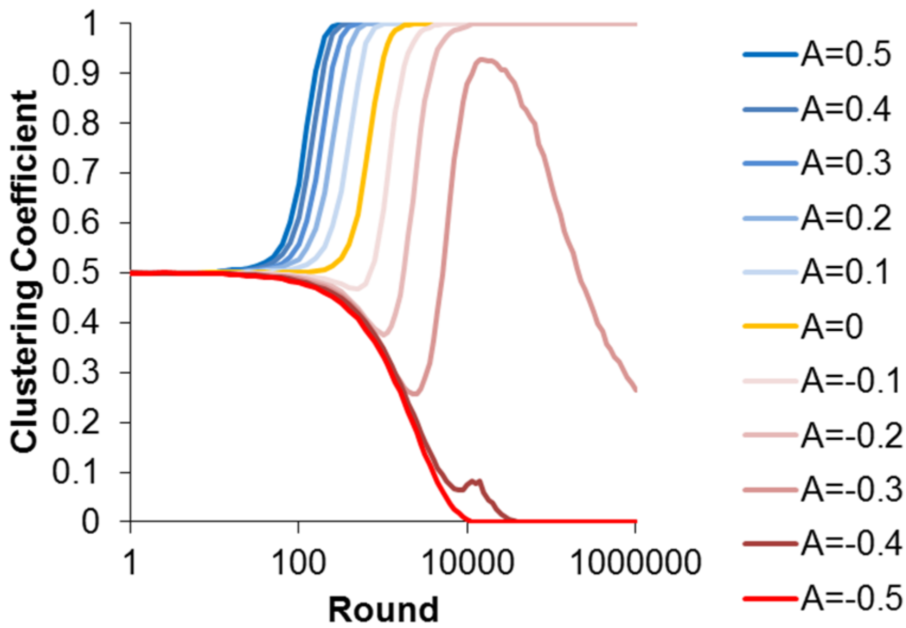

Figure 6. The genesis of groups through time, across variations in baseline trust/suspicion (*A*). Each line averages 10,000 simulation runs using *N*=50, *r*=3 and *t*=2. X-axis is log10-scaled.

General Discussion

Our model provides a simple but powerful to study group genesis, revealing not only the necessary conditions for group formation, but also the configuration of groups, the influence of group-promoting conditions on individual payoffs, and the impact of trust. Our results suggest that groups robustly form under conditions of reciprocity (*r*) and transitivity (*t*), for all observed population sizes (*N*). Despite high variability across individual simulations, group structure is robust to varying parameter values of reciprocity and transitivity, and responds systematically to population size. Analyses of individual payoffs suggest that conditions for group genesis are adaptive, and manipulating psychological context—trust versus suspicion (*A*)—coherently interacts with group formation. Our agent-based model provides a parsimonious explanation for group genesis: reciprocity and transitivity combine over time to bind together selfish, identical and identity-blind agents into distinct clusters.

Consistent with these results, research documents robust group formation under conditions of reciprocity and transitivity in relatively homogeneous real-world populations, including hunter-gatherers in Tanzania (Apicella, Marlowe, Fowler, & Christakis, 2012), EMBA students at a mixer (Ingram & Morris, 2007), and monk-novitiates at an American monastery (Sampson, 1969; visualized in Figure 7). In addition, research has documented the power of reciprocity and transitivity to amplify group formation in social networks—transforming even modest degrees of in-group preference into striking patterns of segregation (Kossinets & Watts, 2009; Wimmer & Lewis, 2010). To our knowledge, our research is the first to bridge these two sets of findings and demonstrate robust group emergence groups in a fully homogeneous population.

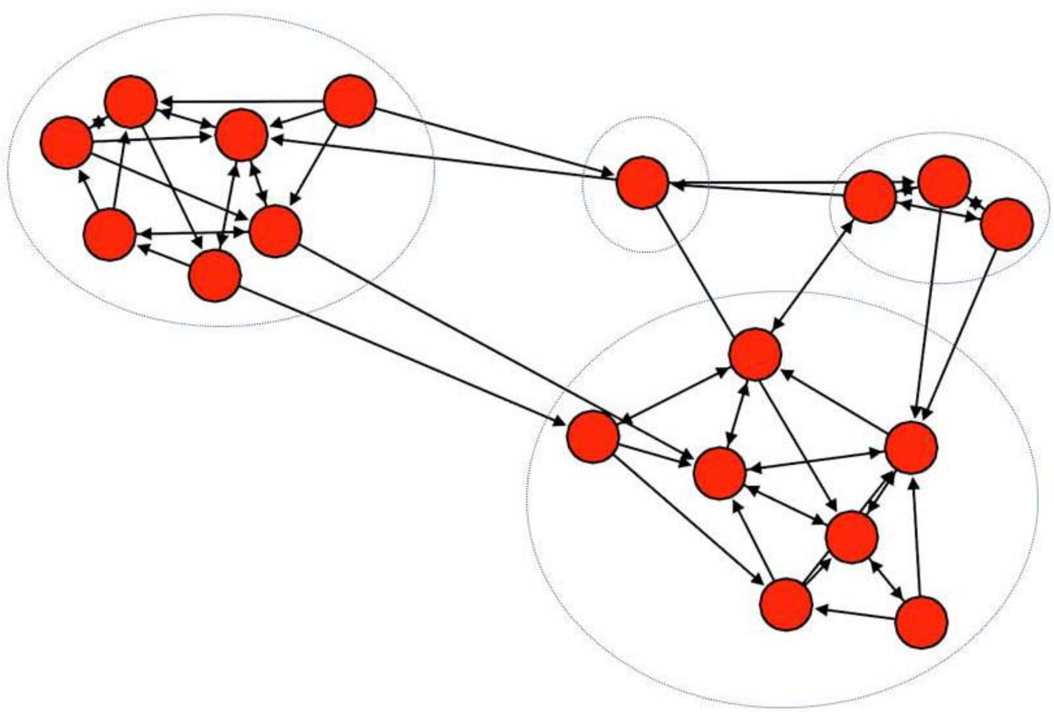

Figure 7. Endogenous group genesis within a relatively homogeneous population of monks within a single monastery (Sampson, 1969). Each dot represents a single monk, and arrows represent ties between monks. Broader circles represent overarching clusters (i.e., groups.)

The work provides a first simple step in modeling group genesis, and future models should explore more complex scenarios, such as multi-group formation (i.e., multiplexity; Krohn, Massey, & Zielinski, 1988) because individuals typically belong to multiple groups across different social contexts (e.g., work units, friendship groups, and athletic teams). Smaller groups (e.g., state Democrats) are also often subsumed within larger groups (e.g., national Democrats), and so future research might also examine hierarchical group formation. More complex reciprocity rules could also be examined. For simplicity, our model assumes that interpersonal closeness remains constant after a prisoner's dilemma with one cooperator and one defector. As research points to the relative power of negativity over positivity (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001), we ran new simulations in which defection was relatively more powerful than cooperation: when one player cooperates and the other defects, the two players move somewhat further apart. Consistent with earlier results, stable groups formed, although the clustering coefficient took a small initial dip (from .50 to .43) before proceeding monotonically to maximum clustering (at 1.00) as before. Finally, model complexity could be increased by moving from dyadic interactions to multi-player interactions. In the supplementary materials, we generalize the model from prisoner's dilemmas to *n*-player public goods games, and again document robust group genesis.

Phenomena across levels

Our research highlights the importance of understanding social phenomena across levels (Bonabeau, 2002; Brewer, 2013; Gray, Young, & Waytz, 2012; Macy & Willer, 2002; A. Nowak et al., 1990; Smith & Conrey, 2007; Vallacher et al., 2002). In isolation, factors such as reciprocity and transitivity may seem insufficient for group formation, but research has highlighted the ability for complex higher-level phenomena to emerge from simple lower-level principles (Sawyer, 2005; Vallacher et al., 2002; Veelen, García, Rand, & Nowak, 2012). For example, research on social physics explains phenomena ranging from which direction people face at music festivals to why people fidget more before groups dissolve (Pennebaker, 2003).

Agent-based models allow us to understand both the configuration and variability of group formation across a variety of parameters. These are difficult to examine in the lab due to the vast number of participants required for reliable effect estimates, and because—due to randomness and path-dependence—group configurations are sensitive to the outcome of initial interactions (Ingram & Morris, 2007). Previous modeling has also investigated group genesis (e.g., Efferson et al., 2008; Schelling, 1969, 1971), however, unlike these investigations—which rely on pre-existing differences (Efferson et al., 2008; i.e., race; Schelling, 1971)—we show that individual behaviors can aggregate to group formation even in completely homogeneous populations. These results provide a parsimonious account of group genesis and a model for future research, with available source code and an interactive site to stimulate novel theory and applications.

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